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An Intelligent Scheduling Strategy of Collaborative Logistics for Mass Customization

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Abstract

To improve the scheduling optimization of mass customization collaborative logistics, a scheduling solution developed based on the novel particle swarm optimization algorithm was proposed. A mathematic model based on scheduling strategy of mass customization logistics was designed. The novel dynamic particle swarm optimization algorithm framework was given. And simulation experiments were done to validate algorithm. Experiment results show that the proposed algorithm effectively improves the scheduling optimization of mass customization collaborative logistics, which has direct applications for Logistics scheduling

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Keyword: Particle swarm optimization algorithm; Mass customization collaborative logistics; Logistic scheduling

1. Introduction

Optimization of logistics support aims to reduce operation costs for the service providers without sacrificing the quality of services to customs. With the influence of enterprise size, specialty of the product and other factors, clients had different needs and expectations for logistics services, such as reducing stock levels, quick response markets etc. Logistics service providers therefore seek for improved scheduling, and customized solutions to meet a wide range of customer demand. The goal of logistics optimization of mass customization is to incorporate modern logistics and information technology and advanced logistics management concept, through the optimal allocation of limited resources of network

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members, in order to reduce large-scale operation cost and to increase the efficiency for providing customized logistics services to customers. In recent years, scheduling optimization of logistics supply had the great attention and received considerable development by the domestic and international logistics industry. Logistics scheduling optimization also attracted wide attention from scholars. Previous studies [1] proposed a hybrid multi-objective optimization algorithm; literature [2] proposed a modified particle swarm algorithm, which combines the mutation operation to improve the performance of particle swarm algorithm. Literature [3] analyzing the status of food logistics, proposed the optimal scheduling of logistics based on an ant colony algorithm to realize the dynamic process of food distribution. Literature [4] proposed an improved ant colony algorithm to solve the logistics problems of route optimization.

2. The mathematical model of Mass customized logistics scheduling

To elucidate the theoretical background of the model, we used supplier coordination of multiple logistics nodes together as an example. The goal here is to demonstrate how mathematically the model is able to effectively accomplish a number of customized logistics tasks. Suppose a main supplier received N task within a time domain, $R = \{r_i \mid 1 \leq i \leq N\}$ such as purchasing, supply, distribution etc; each task r_i composed by the sequence of activities that constitute theirs. $r_i = \{a_{ij} \mid 1 \leq i \leq N, 1 \leq j \leq L_i\}$, such as Order processing, packaging, handling, transportation, storage, sales return processing, etc. each task r_i Have a deadline d_i . Each activity a_{ij} by different nodes performed in logistics network $p (1 \leq p \leq M)$, Since each node to use different resources and costs, Each activities has a set of execution mode U_{ij} , One element of u_{ijp} express activity a_{ij} excused by node p ; node p execute activities a_{ij} the cost denoted by c_{ijp} , Consumption of times denoted by t_{ijp} , the start time is s_{ijp} . Since each logistics node can be process for different tasks at different times, the goal of coordinated decision is to determine that the Order of execution, execution mode and start time in network node of the logistics activities and Make collaborative logistics network is optimal for the total cost of implementation of the activities and the total time.

In the Task r_i the Time constraints L_i square matrix of between the various logistics activities $K^i = (k_{gh}^i)_{L_i \times L_i}$, k_{gh}^i See Equation (1).

$$k_{gh}^i = \begin{cases} 1, & \text{if } a_{ig} \text{ before } a_{ih} \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

Logistics network nodes to perform activities as u_{ijp} , See Equation(2)

$$u_{ijp} = \begin{cases} 1, & \text{if node } p \text{ run activity } a_{ij} \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

In this paper, the mathematical model of large-scale customized logistics scheduling problem as follows,

$$\begin{aligned} \min y = & w_1 \sum_{i=1}^N \sum_{j=1}^{L_i} \sum_{p=1}^M c_{ijp} u_{ijp} + w_2 \sum_{i=1}^N \sum_{j=1}^{L_i} \sum_{p=1}^M t_{ijp} u_{ijp} \\ & + v \sum_{i=1}^N \max \left(\sum_{j=1}^{L_i} \sum_{p=1}^M t_{ijp} u_{ijp} - d_i, 0 \right) \end{aligned} \quad (3)$$

$$\sum_{i=1}^N \sum_{j=1}^{L_i} \sum_{p=1}^M u_{ijp} = \sum_{i=1}^N L_i, \quad u_{ijp} \in \{0, 1\} \quad (4)$$

$$s_{igp} - s_{ihp} \geq t_{ijp}, \text{ 若 } k_{gh}^i = 1 \quad (5)$$

Equation(3) is the objective function, w_1, w_2 is the weighting factor of cost and time, v is the Penalty factor of time delay; Equation(4) ensure that each logistics activities execution by a node in logistics network. Equation (5) ensure that the same logistics tasks between the various logistics activities to settle for the time constraints.

The mass customized logistics scheduling algorithm based on Dynamic Particle Swarm

Particle groups in the D-dimensional space flight, The location of particle i is $x_i = (x_{i1}, x_{i2}, \dots, x_{iD})$, the flight speed is $V_i = (v_{i1}, v_{i2}, \dots, v_{iD})$, The optimal position for the flight is $P_i = (p_{i1}, p_{i2}, \dots, p_{iD})$, among them, $i = 1, 2, \dots, k$. The Groups of particles through the optimal position is $P_g = (p_{g1}, p_{g2}, \dots, p_{gD})$. Particle updates its velocity and position according to the following formula in the process of group fly to optimal position.

$$v_i(t+1) = w \cdot v_i(t) + c_1 r_1 (p_i - x_i(t)) + c_2 r_2 (p_g - x_i(t)) \quad (6)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (7)$$

Among them, w is inertia weight, Indicate that the influence of history of particle velocity to the current speed. c_1, c_2 is the acceleration factor, r_1, r_2 is the Random number among $[0,1]$. The second of speed formula(6) indicate the individual particles Cognitive; The second indicates Social cognition. The partial swarm algorithm based on formula (6)、(7) called basis partial swarm algorithm.

The basic particle swarm algorithm has slow convergence speed, likely to fall into local optimum and other defects. In this paper a dynamic multi-species particle swarm algorithm was designed.

In this algorithm, firstly, the particles search for target in the groups. When the fitness value is less than a threshold, changes in particle swarm search stagnation occur and particle groups would be divided into two subgroups. Particle clustering, the individual fitness value according to subgroup allocation: the highest fitness value assigned to the first sub-group of particles, followed by the fitness value assigned to the second sub-group of particles, according to the principle of distribution of the remaining particles assigned to each subgroup. This clustering method is better achieved in different subgroups of individuals within the uniform distribution. After the particle distribution, subgroup will search target individually.

Algorithm by continuous population subgroup with optimal dynamic mix for target optimization, until the termination conditions are met. This algorithm is part of the sub-group re-initialized particle pairs with alternative measures equivalent to a mutation cluster particles, and the subgroup of hybrid evolutionary measures equivalent to the two subgroups for cross-operation.

This sub-group design particle velocity and position update formula such as Formula (8) and formula (9)

$$v_{i,j}(t+1) = w(t) \cdot v_{i,j}(t) + c_3 r_3 (p_{i,j}(t) - x_{i,j}(t)) + c_4 r_4 (p_{g,j}(t) - x_{i,j}(t)) \quad (8)$$

$$x_{i,j}(t+1) = x_{i,j}(t) + v_{i,j}(t+1) \quad (9)$$

Among, $i=1, \dots, m$ is the number of particles in the sub-group, $j=1, 2$ is the number of subgroups. $v_{i,j}(t)$ is the i particle Flight speed in j sub-group. $p_{g,j}(t)$ is the global best position from j subgroups evolved to t , $p_{i,j}(t)$ is the optimal position of the individual from j subgroups evolved to t . c_3, c_4 is the acceleration factor, r_3, r_4 is the random number among $[0,1]$.

3. Experimental results and analysis

To validate the design performance of the logistics scheduling algorithm, the two set of experiments. the first experiments: Verify the effectiveness of the algorithm. Experiments described below: A logistics company in the time domain of logistics tasks for the six series of activities in the seven co-ordination division of network nodes. Key data such as shown in Table 1 and Table 2. w_1 , w_2 is used to control the coordination of decision-making time and cost of weight, Core logistics service providers can customize the logistics needs of different customers, for w_1 , w_2 dynamic adjusted.

Table 1 The time parameters of collaborative logistics activities

	T1			T2			T3			T4		T5				
	T11	T12	T13	T21	T22	T23	T31	T32	T33	T41	T42	T51	T52	T53	T54	
N1	5	6	-	10	5	4	-	7	8	-	6	-	-	-	-	20
N2	7	-	5	9	7	-	11	8	-	12	8	-	-	-	-	17
N3	8	-	7	-	4	-	-	9	5	-	-	9	-	7	-	-
N4	-	7	6	8	-	-	-	6	-	-	-	-	4	6	-	-
N5	-	5	-	7	-	6	-	-	-	10	-	7	6	8	-	-
N6	6	8	8	-	-	5	10	-	-	-	-	6	7	-	-	18
N7	7	-	-	11	-	7	12	-	7	14	7	-	-	-	-	-

Table 2 The cost parameters of collaborative logistics activities

	T1			T2			T3			T4		T5				
	T11	T12	T13	T21	T22	T23	T31	T32	T33	T41	T42	T51	T52	T53	T54	
N1	17	14	-	15	19	15	-	12	37	-	90	-	-	-	-	40
N2	20	-	11	14	17	-	79	11	-	58	81	-	-	-	-	47
N3	19	-	13	-	18	-	-	9	35	-	-	49	-	27	-	-
N4	-	15	12	13	-	-	-	13	-	-	-	-	14	24	-	-
N5	-	16	-	12	-	13	-	-	-	52	-	47	17	25	-	-
N6	19	13	14	-	-	14	81	-	-	-	-	51	16	-	-	45
N7	18	-	-	16	-	16	82	-	41	64	76	-	-	-	-	-

Using this algorithm, the optimization of logistics and scheduling tasks, the results shown in Table 3

Table 3 This paper Scheduling algorithm results

Time constraints	[19,18,25,18,50]
Execution time	109
Implementation costs	473
Execution order	T21 ,T23,T11,T41,T12,T42,T51,T54,T31,T13,T22,T52,T32,T53,T33
Execution mode	N4,N6,N7,N5,N1,N7,N5,N6,N2,N2,N3,N4,N1,N5,N3

As can be seen from Table 3, the algorithm can effectively solve large-scale customized logistics scheduling problem.

Experimental Group 2: Scheduling tasks in multiple combinations, Genetic algorithms and compare the performance of this algorithm, The maximum number of iterations the two algorithms were 700-generation. Literature algorithm group size is 100, Mutation and crossover probabilities were 0.8 and 0.05; The number of particles of this algorithm is 100. Number of iterations is 2000, Acceleration factor $c_1 = 2.0$, $c_2 = 2.0$, $c_3 = 2.0$, $c_4 = 2.0$, Inertia weight W from 0.9 down to 0.4, When the five generations of the evolution of populations to adapt to changes in the value of less than 5% then clustering optimization, When the subgroup of five generations of evolution to adapt to changes in the value of less than 5%, Subgroup 1, the worst fitness value of 10% re-initialize the particles, 40% of subgroup 2, the worst fitness value of particles is the same number of particles of high fitness alternative. Two algorithms were run independently 100 times, averaging the results, as shown in Table 4.

Table 4 This paper algorithm performance comparison with the literature

Numbers of tasks	The numbers of activities for each task	Optimal decision-making Average of the required algebraic		Optimal for decision-making Average time (seconds)	
		Genetic algorithm	This Algorithm	Genetic algorithm	Genetic algorithm
20	15	154.25	97.73	21.45	17.46
30	20	402.78	317.43	57.76	43.56
40	30	505.38	425.34	97.28	70.41
50	35	609.35	534.45	116.89	94.34

It can be seen from Table 4: task scheduling in all combinations, optimal decisions, the algorithm is less than the required number of iterations the genetic algorithm, the algorithm running time is less than the required GA; This shows that this algorithm is superior to genetic algorithm.

Conclusion

An effective logistics supply system is important to the sustainable development of a modern society. This paper demonstrates a logistics supplying framework for mass customization that minimizes operation costs and delivery time. The proposed modeling framework integrates the target evaluation index of large-scale customized logistics coordination into a mathematical model, and then constructs a solution to optimize collaborative decision-making that further improves particle Swarm Optimization commonly used for logistics coordination. Simulations show that the algorithm can effectively solve the coordination of logistics in the logistics node selection and node cooperation coordination of scheduling optimization problems.

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